

# Event-based computation: Unsupervised elementary motion decomposition

Petrut A. Bogdan

*School of Computer Science  
The University of Manchester  
Manchester, UK*

petrut.bogdan@manchester.ac.uk

Garibaldi Pineda García

*School of Engineering and Informatics  
University of Sussex  
Brighton, UK*

g.pineda-garcia@sussex.ac.uk

Simon Davidson

*School of Computer Science  
The University of Manchester  
Manchester, UK*

simon.davidson@manchester.ac.uk

Michael Hopkins

*School of Computer Science  
The University of Manchester  
Manchester, UK*

michael.hopkins@manchester.ac.uk

Robert James

*School of Computer Science  
The University of Manchester  
Manchester, UK*

robert.james@manchester.ac.uk

Steve B. Furber

*School of Computer Science  
The University of Manchester  
Manchester, UK*

steve.furber@manchester.ac.uk

**Abstract**—Fast, localised motion detection is crucial for an efficient attention mechanism. We show that modelling a network capable of such motion detection can be performed using spiking neural networks simulated on many-core neuromorphic hardware. Moreover, highly sensitive neurons arise from the presented network architecture through unsupervised self-organisation. We use a synaptic rewiring rule which has been shown to enable the formation and refinement of neural topographic maps. Our extension allows newly formed synapses to be initialised with a delay drawn from a uniform distribution. Repeated exposure to moving bars enables neurons to be sensitised to a preferred direction of movement. Incorporating heterogeneous delays results in more sensitive neural responses. A readout mechanism involving a neuron for each learnt motion is sufficient to establish the input stimulus class.

**Index Terms**—SpiNNaker, Neuromorphic computing, Spiking Neural Network, structural plasticity, synaptic rewiring, topographic maps

## I. INTRODUCTION

Neuromorphic platforms are relatively novel computational systems designed to mimic key aspects of mammalian brain operation: massive parallelism, low energy consumption, fault tolerance and sparsity. These platforms come in multiple flavours ranging from full-custom chip design (mixed analogue-digital [1] and fully digital designs [2]) to using a vast array of off-the-shelf components. SpiNNaker [3] (the full system is pictured in Fig. 1) is a digital many-core neuromorphic platform designed to simulate a vast number of biologically-inspired spiking neurons in real time.

Novel computing architectures require the development of new methodologies and tools to harness their full capabilities.

The design and construction of the SpiNNaker machine was supported by EPSRC (the UK Engineering and Physical Sciences Research Council) under grants EP/D07908X/1 and EP/G015740/1, in collaboration with the universities of Southampton, Cambridge and Sheffield and with industry partners ARM Ltd, Silistix Ltd and Thales. Ongoing development of the software is supported by the EU ICT Flagship Human Brain Project (H2020 785907), in collaboration with many university and industry partners across the EU and beyond.



Fig. 1: The 1 million ARM-core SpiNNaker machine. Capable of simulating on the order of 200 million neurons, with 1,000 synapses each, in real-time.

While using ARM technology for the 18 computational cores present on chip, SpiNNaker has been designed specifically for spiking neural network (SNN) simulations using a purpose-built router and attaching small amounts of fast memory to each individual core.

We build on previous work [4] and present an end-to-end approach to perform elementary motion decomposition using leaky integrate-and-fire neurons and structural and synaptic plasticity [5]. Further, the computational platform which is the basis for these simulations is event-driven [6], including the spiking visual input provided to the network. The biologically inspired sensory processing method presented here is an alternative to traditional frame-based computer vision.

We show that (1) the presented architecture allows for unsupervised learning; that (2) synaptic rewiring enhanced to initialise synapses by drawing from a distribution of delays produces more specialised neurons; and that (3) a pair of readout neurons is sufficient to correctly classify the input based on the target layer’s activity using rank-order encoding (first classification neuron to spike wins), rather than spike-rate encoding (classification neuron which fires most in a time period wins).

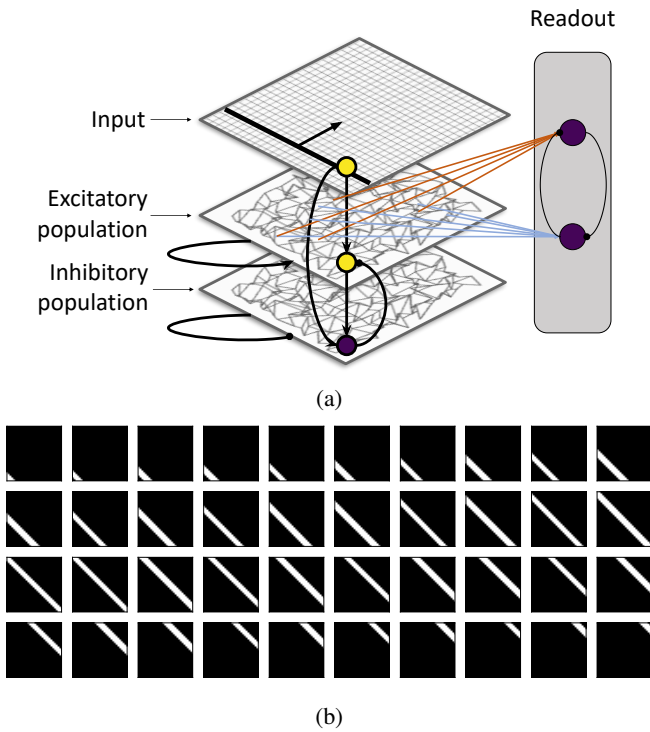


Fig. 2: (a) Network architecture. (b) Example input 45° degree movement represented as its constituent frames (before processing to generate spikes). A new frame is presented every 5 ms and, in total, the presentation of an entire pattern takes 200 ms.

## II. METHODS

The SNN architecture (pictured in Fig. 2a) is designed to allow unsupervised learning through self-organisation using synaptic and structural plasticity mechanisms [5]. Neurons in the two target populations are modelled as being positioned at integer locations on a  $32 \times 32$  grid with periodic boundary conditions. The excitatory population contains neurons which receive sparse excitatory connections from the input layers and from themselves, while projecting to the inhibitory layer and to the readout neurons responsible for the final motion classification decision. The inhibitory population follows a similar structure, but only projects using inhibitory synapses. Very strong inhibition is also present between the readout neurons, implementing a winner-takes-all circuit. The networks are described using the PyNN simulator-independent language for building neuronal network models [7] and the SpiNNaker-specific software package for running PyNN simulations (sPyNNaker [6])<sup>1</sup>. The model is simulated in real time on the SpiNNaker many core neuromorphic platform using previously presented neuron and synapse dynamics [5].

The input stimulus consists of bars encoded using spikes representing “ON” and “OFF” pixels (see Fig. 2b for an example before filtering using a previously described technique [8])

<sup>1</sup>The data and code used to generate the results presented in this paper are available from doi: 10.17632/wpzxh93vnx.1

as well as a background level of Poisson noise (5 Hz). Each stimulus is presented over a 200 ms time period always moving at a constant speed (200 frames per second). During training the target layers are presented with bars moving in two directions (Eastward or at 0° and Northward or at 90°), but during testing they are presented with moving bars in all directions (randomised over time, in 5 degree increments) – weights and connectivity are fixed during this latter phase. The simulations are initialised with no connections and are trained for around 5 hours, while testing occurs over 20 minutes. As a result of the chosen testing regime, the networks sees over 80 moving bar presentations at each of the 72 angles. This allows us to perform a *pair-wise independent t-test* between the responses at each of the angles in the two cases and establish whether their responses are statistically different. The readout neurons are trained and tested separately from the rest of the network – this process takes on the order of a minute.

Using the structural plasticity mechanism implemented for SpiNNaker, new synapses are formed in two regimes: with heterogeneous, random delays ([1, 15] ms, uniformly drawn) and homogeneous, constant (1 ms) delays; the latter is taken to be the control experiment. Further, according to the structural plasticity mechanism, depressed synapses are more likely to be removed. This optimises the use of the limited synaptic capacity available for each post-synaptic neuron [9]; neurons have a fixed maximum fan-in of 128 synapses with delays which do not change over time.

The direction selectivity index (DSI) will be computed for each neuron after training:  $DSI = (R_{pref} - R_{null}) / R_{pref}$ , where  $R_{pref}$  is the response of a neuron in the preferred direction, and  $R_{null}$  is the response in the opposite direction [10]. We compute it for each of the possible directions and establish the preferred direction as that which maximises the DSI after performing a weighted average of neighbouring responses, reducing the influence of noise.

## III. RESULTS

The response of the excitatory population in each regime (incorporating heterogeneous delays or not) is plotted for each testing direction (minimum, mean and maximum responses presented in Fig. 3a). The polar plot reveals the firing rate (Hz) of neurons during testing when the input is moving in each of the 72 directions from 0° to 355° in 5° increments in a random order. The network response shows that neurons are responding preferentially to movement, rather than simply to the shape of the input, because the response is asymmetrical – it can differentiate between e.g. a vertical bar moving Eastward and the same vertical bar moving Westward. The *pair-wise independent t-test* is performed to compare the network response in the two regimes (Fig. 3c, red line signifies that  $p \geq 0.001$  for that particular angle); the response is higher in one training direction (90°) and less in the other (0°) for the network with heterogeneous delays compared to the control. As such, we proceed by examining individual neurons rather than the average network behaviour. The spatial organisation of neurons and their preferred angle is presented in Fig. 3b, showing that

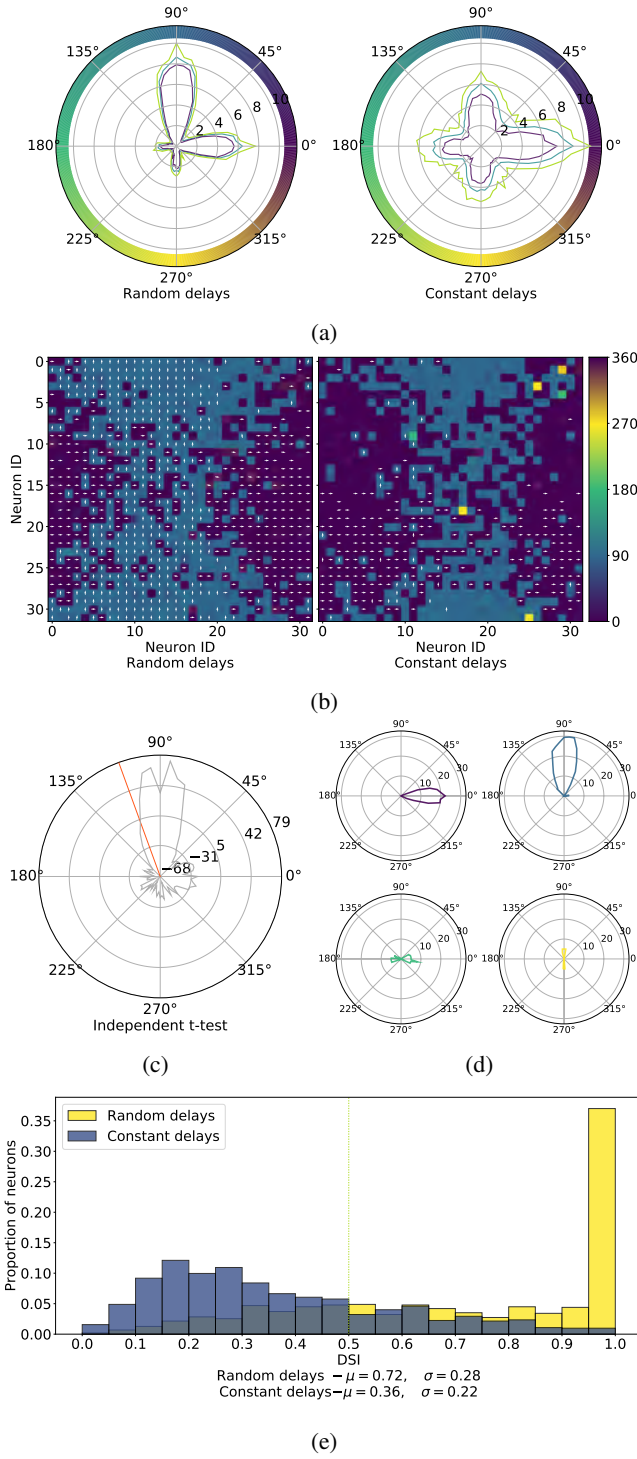


Fig. 3: (a) – minimum, mean and maximum aggregate excitatory population firing response (Hz); (b) – neuron angle preference based on maximum firing rate (the colour) and DSI (the arrow is present if  $DSI \geq 0.5$ ); (c) – *pair-wise independent t-test* comparing the network with heterogeneous delays (on the left in a and b) compared to the control, red lines = insignificant results; (d) – selected individual neuron responses (random delays); (e) – DSI distribution comparison.

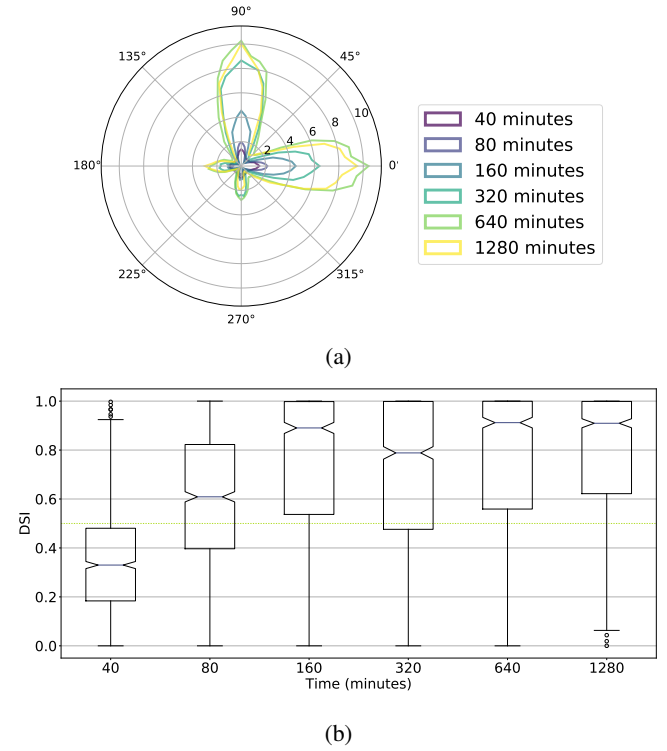


Fig. 4: Network behaviour evolution with longer simulation run times. (a) – average network firing response during inference when trained for ever increasing times; (b) – DSI distribution displayed as a *boxplot* for each simulation in (a). Note: Each data point is a different simulation.

local neural neighbourhoods become sensitised to the same input statistics. There we also look at neurons' maximum responses (encoded by the colour of the cell) in conjunction with the direction which maximises DSI (arrow direction) and  $DSI \geq 0.5$  (arrow presence). The direction selectivity index histogram presented in Fig. 3e. compares the two networks; the control network has significantly fewer selective neurons (251 compared to 744) and selectivity is lower on average. Individual responses of our simulated neurons resemble the direction selectivity found in Superior Colliculus [11].

Further, we examine the network behaviour over a wide range of simulations times, ranging from 40 minutes up to 20 hours. Figure 4a shows the evolution of the population-level firing rate and the evolution of the DSI metric (Fig. 4b). The network is thus shown to be stable over long periods of time, rather than showing destructive dynamics.

A readout or classification mechanism relying on 2 mutually inhibitory neurons is sufficient to resolve the two directions presented in the input. Static excitatory connectivity originating from the excitatory layer results in a potential 100% classification accuracy based on rank-order encoding. After 40 seconds, the two neurons have self-organised to respond to one of two input patterns. Figure 5 shows the spiking behaviour of the two neurons in the first 1.8 seconds of training and testing. Spike-timing dependent plasticity (STDP) reduces the

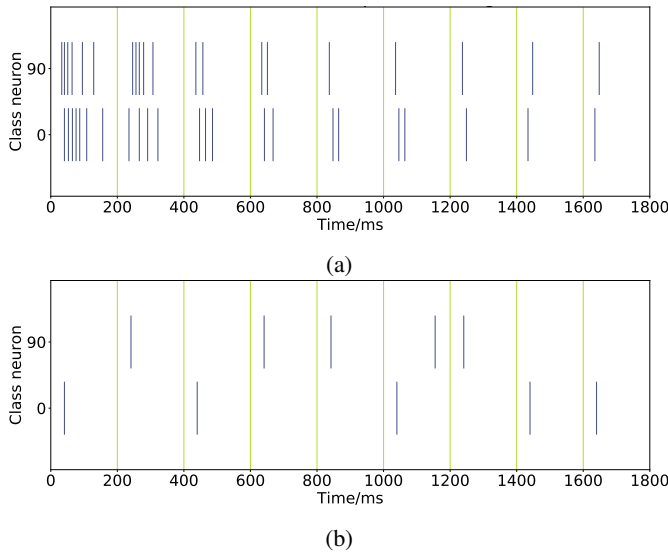


Fig. 5: Initial spiking activity of the two readout neurons during training (a) and testing (b). The full-height vertical bars denote the edges of the pattern presentation time bins (every  $t_{stim} = 200$  ms). Neuron class is established post-hoc as the one which maximises classification accuracy.

latency in neural response to the stimuli, making the neurons respond to the stimulus onset, thus making them ideal for classification using rank-order encoding, rather than a winner-takes-all classification based on spike count across a time period [4].

#### IV. DISCUSSION

We have shown that neurons become sensitised in an unsupervised manner to bars moving in various directions through local learning mechanisms and an interplay between lateral excitation and inhibition. They self-organise their connectivity through synaptic plasticity and rewiring. The rewiring rule with heterogeneous delays selects ideal spatial distributions of synaptic delays driven by STDP. With the current experimental setup, two readout neurons are sufficient for accurate classification of input bar movement direction.

Future work will focus on processing larger and more realistic scenes, as well as handwritten digits. For this, the output layer could be enhanced to produce a correct readout more consistently, e.g through the use of populations of neurons rather than individuals; readout populations would also allow the encoding of the location in the receptive field of the moving bar, rather than its current status as a binary flag of whether a specific movement direction is presented in the input. The readout layer would eventually be replaced entirely using the structures as presented herein to form a more complete visual cortex model. Finally, we will explore further means to control the response of neurons and ensure maximum selectivity for them all.

#### REFERENCES

- [1] J. Schemmel, L. Kriener, M. Paul, K. Meier, P. Müller, K. Meier, M. Paul, and K. Meier, “An Accelerated Analog Neuromorphic Hardware System Emulating NMDA- and Calcium-Based Non-Linear Dendrites,” *arXiv preprint arXiv*, vol. 1703, no. 07286, pp. 2217–2226, may 2017.
- [2] M. Davies, N. Srinivasa, T.-h. H. Lin, G. Chinya, Y. Cao, S. H. Choday, G. Dimou, P. Joshi, N. Imam, S. Jain, Y. Liao, C.-k. K. Lin, A. Lines, R. Liu, D. Mathiakutty, S. McCoy, A. Paul, J. Tse, G. Venkataramanan, Y.-h. H. Weng, A. Wild, Y. Yang, H. Wang, I. Labs, and I. Corporation, “Loihi: A Neuromorphic Manycore Processor with On-Chip Learning,” *IEEE Micro*, vol. 38, no. 1, pp. 82–99, 2018.
- [3] S. B. Furber, D. R. Lester, L. A. Plana, J. D. Garside, E. Painkras, S. Temple, and A. D. Brown, “Overview of the SpiNNaker system architecture,” *IEEE Transactions on Computers*, vol. 62, no. 12, pp. 2454–2467, 2013.
- [4] M. Hopkins, G. Pineda-García, P. A. Bogdan, and S. B. Furber, “Spiking neural networks for computer vision,” *Royal Society Interface Focus*, vol. 8, no. 4, mar 2018.
- [5] P. A. Bogdan, A. G. D. Rowley, O. Rhodes, and S. B. Furber, “Structural plasticity on the SpiNNaker many-core neuromorphic system,” *Frontiers in Neuroscience*, vol. 12, no. 12, pp. 1–20, 2018.
- [6] O. Rhodes, P. A. Bogdan, C. Breninkmeijer, S. Davidson, D. Fellows, A. Gait, D. R. Lester, M. Mikaitis, L. A. Plana, A. G. D. Rowley, A. B. Stokes, and S. B. Furber, “sPyNNaker : A Software Package for Running PyNN Simulations on SpiNNaker,” *Frontiers in Neuroscience*, vol. 12, no. November, 2018.
- [7] A. P. Davison, P. Andrew, D. Brüderle, J. Eppler, J. Kremkow, E. Muller, and D. Pecevski, “PyNN: a common interface for neuronal network simulators,” *Frontiers in Neuroinformatics*, vol. 2, no. January, pp. 1–10, 2008.
- [8] G. Pineda Garcia, P. Camilleri, Q. Liu, and S. Furber, “pyDVS: An extensible, real-time Dynamic Vision Sensor emulator using off-the-shelf hardware,” in *IEEE Symposium Series on Computational Intelligence, SSCI*, 2016.
- [9] R. George, G. Indiveri, and S. Vassanelli, “Activity Dependent Structural Plasticity in Neuromorphic Systems,” in *Biomedical Circuits and Systems Conference (BioCAS)*. Torino, Italy: IEEE, 2017, pp. 1–4.
- [10] M. Mazurek, M. Kager, and S. D. V. Hooser, “Robust quantification of orientation selectivity and direction selectivity,” *Frontiers in Neural Circuits*, 2014.
- [11] S. Inayat, J. Barchini, H. Chen, L. Feng, X. Liu, J. Cang, X. S. Inayat, J. Barchini, X. H. Chen, L. Feng, X. Liu, and X. J. Cang, “Neurons in the Most Superficial Lamina of the Mouse Superior Colliculus Are Highly Selective for Stimulus Direction,” *Journal of Neuroscience*, vol. 35, no. 20, pp. 7992–8003, 2015.